Hybrid horned lizard optimization algorithm-aquila optimizer for DC motor

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ABSTRACT

This research presents a modification of the horned lizard optimization (HLO) algorithm to optimize proportional integral derivative (PID) parameters in direct current (DC) motor control. This hybrid method is called horned lizard optimization algorithm-aquila optimizer (HLAO). The HLO algorithm models various escape tactics, including blood spraying, skin lightening or darkening, crypsis, and cellular defense systems, using mathematical techniques. HLO enhancement by modifying additional functions of aquila optimizer improves HLO performance. This research validates the performance of HLAO using performance tests on the CEC2017 benchmark function and DC motors. From the CEC2017 benchmark function simulation, it is known that HLAO's performance has promising capabilities. By simulating using 3 types of benchmark functions, HLOA has the best value. Tests on DC motors showed that the HLAO-PID method had the best integrated of time-weighted squared error (ITSE) value. The ITSE value of HLOA is 89.25 and 5.7143% better than PID and HLO-PID.

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1. INTRODUCTION

Due to factors such as urbanization, industrialization, and population growth, the global energy demand has been steadily rising over the last ten years. This has placed a great deal of strain on energy security, production, pollution emissions, and climate change. The first step in relieving the stresses brought on by rising energy usage in many nations throughout the world has been to improve energy efficiency [1], [2]. The process of maintaining ecosystems by the wise use and replenishment of the natural resources that sustain life on Earth is known as environmental sustainability [3]. The United Nations' Sustainable Development Goal 7 (clean and accessible energy) includes energy efficiency, which is essential to environmental sustainability [4], [5].

Electrical energy efficiency is an effort made to reduce the amount of energy needed to use an efficient electrical energy system. In this context, an electrical energy system can be said to be efficient if the electrical energy produced is clean and stable. Electrical energy efficiency also has benefits for national

security because it can be used to reduce import levels [6]–[8]. The use of electrical energy efficiency technology, such as control and regulation systems, aims to reduce energy use [9], [10].

Because of their great efficiency, accurate control, and versatility in operation, direct current (DC) motors find extensive use across a range of sectors. The automotive industry, robotics, electric vehicles, and hoists and cranes are a few of the principal uses for DC motors [11]. By precisely regulating the voltage and current, DC motors enable effortless speed control both above and below the rated speed [12]. Unlike alternating current (AC) induction motors, which can result in issues like torque pulsation, warmth, noise, and a decreased power factor (PF), DC motors do not emit any harmonics. Because of their straightforward construction, DC motors are simple to service and maintain. DC motors have applications in diverse areas such as renewable energy systems, robotics, automotive, and industrial automation.

Proportional integral derivative (PID) control is a control technique commonly used in various research topics, including DC motor speed control. In PID control, the steady state error (error that does not change) can be adjusted by selecting the appropriate proportional (P), integral (I), and derivative (D) correlations [13]. In PID control, the correlation P, I, and D are used together to regulate the steady state error, rise time, and settling time (the time required to reach the steady state error) [14]. The weakness of conventional DC motor control with PID is that PID can cause over-shoot, PID can cause an unstable system, namely a system that cannot regulate speed correctly and PID can require correct tuning to regulate the correlation of P, I, and D, which requires time and skill [15].

Several DC motor control techniques using optimized PID have been presented. Optimization techniques using computing have been widely applied, such as particle swarm optimization (PSO) [16], [17], firefly algorithm [18]–[20], equilibrium optimizer [21], gray wolf optimization [22], and transit search optimization algorithm [23]. There is still much to learn about DC motor control, despite the presentation of multiple optimal control experiments. To set PID settings for DC motors, this article proposes a control approach based on the horned lizard optimization algorithm-aquila optimizer (HLAO) method. There are two HLAO performance measurements used in this article. The CEC2017 benchmark function test is compared with horned lizard optimization (HLO), a comparison approach, to determine the first performance measurement. In the meantime, HLAO was put to the test for PID-based DC motor control in the second test. In the second test, HLO and the traditional PID approach were employed as comparison techniques. The application of PID control to a DC motor with HLAO is the article's contribution.

The structure of this article is as follows: the HLO algorithm, DC motor, and HLAO are described in section 2. Section 3 is the proposed HLAO for tuning PID in DC motor. In section 4 there are discussions and simulations. The conclusion is presented in the last section.

2. METHOD

2.1. Horned lizard optimization algorithm

The HLO is a metaheuristic optimization system that simulates crypsis, skin lightening or darkening, blood spraying, and mobile defense strategies for escape by mathematical means [24]. When a lizard engages in crypsis behavior, it turns transparent to elude detection by potential predators. In general, HLOA has 6 main strategies used.

2.1.1. First tactic: cryptic conduct

Crypsis is a concept in biology that refers to ability of an organism to hide itself or become invisible to predators or prey. Crypsis is an important survival strategy in nature, which helps organisms to avoid predators and increases their chances of survival and reproduction. This strategy can be modeled in (1) to (9).

$$a^* = \begin{cases} +a, \text{indicates Red} \\ -a, indicates\ Green \end{cases} ;\ b^* = \begin{cases} +b, indicates\ Yellow \\ -b, indicates\ Blue \end{cases} \tag{1}$$
$$c^* = \sqrt{a^{*2} + b^{*2}}$$

$$h = arctg\left(\frac{b^*}{a^*}\right) \tag{2}$$

$$a^* = c^* \cos(h) \tag{3}$$

$$b^* = c^* \sin(h) \tag{4}$$

$$Colorvar_1 = b^*{}_p - a^*{}_q - a^*{}_r + b^*{}_s \tag{5}$$

$$Colorvar_2 = b^*{}_p - a^*{}_q + a^*{}_r - b^*{}_s \quad (6)$$

In (5) and (6) can be represented in one equation, as shown (7).

$$Colorvar = b^*{}_p - a^*{}_q \pm [a^*{}_r - b^*{}_s] \quad (7)$$

The inverse form of (7) is as (8).

$$Colorvar = C_1 \sin(h_p) - C_1 \cos(h_q) \pm [C_2 \sin(h_r) - C_2 \sin(h_s)] \quad (8)$$

Where the angles (hue) fill $h_p \neq h_q \neq \ h_r \neq h_s$ and chroma $c_1 \neq c_2$.

$$C_1 = C_1[\sin(h_p) - C_1 \cos(h_q)] \pm C_2[\cos(h_r) - \sin(h_s)] \quad (9)$$

From (9), the position of the new search agent (horned lizard) in the search solution space $\overrightarrow{x_1}(t+1)$ is obtained in (10).

$$\overrightarrow{x_1}(t+1) = \overrightarrow{x_{best}}(t) + \left(\delta - \frac{\delta.t}{M_{iter}}\right)\left[C_1[\sin(\overrightarrow{x_{r1}}\,(t)) - C_1 \cos(\overrightarrow{x_{r2}}\,(t))] - (-1)^{\sigma}\,(\cos(\overrightarrow{x_{r3}}\,(t)) - \sin(\overrightarrow{x_{r4}}\,(t)))\right] \quad (10)$$

Where a* and b* are the chromatic coordinates. c* and h values correspond to chroma (or saturation) and hue. $\overrightarrow{x_{best}}(t)$ is the best search agent for the generation t. $r_1, r_2, r_3, and\, r_4$ are integer random numbers generated between 1 and the utmost number of search agents with $r_1 \neq r_2 \neq \ r_3 \neq r_4$. M_{iter} represents the utmost number of iterations. σ is a binary value.

2.1.2. Second tactic: darkening or lighting of the skin

Based on whether it needs to reduce or boost its solar thermal gain, the horned lizard can change the color of its skin. The second tactic can be modeled in (11) and (12).

$$\overrightarrow{x_{worst}}(t) = \overrightarrow{x_{best}}(t) + \frac{1}{2}Light_1 \sin(\overrightarrow{x_{r1}}\,(t) - \overrightarrow{x_{r2}}\,(t)) - (-1)^{\sigma}\frac{1}{2}Light_1 \sin(\overrightarrow{x_{r3}}\,(t) - \overrightarrow{x_{r4}}\,(t)) \quad (11)$$

$$\overrightarrow{x_{worst}}(t) = \overrightarrow{x_{best}}(t) + \frac{1}{2}Dark_1 \sin(\overrightarrow{x_{r1}}\,(t) - \overrightarrow{x_{r2}}\,(t)) - (-1)^{\sigma}\frac{1}{2}Dark_1 \sin(\overrightarrow{x_{r3}}\,(t) - \overrightarrow{x_{r4}}\,(t)) \quad (12)$$

Where Lightening1 (0 value) and Lighthening2 (0.4046661 value) are two random numbers created between them. Analogously, Dark1 and Dark2 are arbitrary values that are produced by dividing Darkening1 (value=0.5440510) by Darkening2 (1 value).

2.1.3. Third tactic: squirting blood

The horned lizard shoots blood out of its eyes to ward off enemies. One way to visualize the shooting blood protection mechanism is as a projectile action. It divides the projectile motion into its two components, the X-axis (horizontal) and the Y-axis (vertical), to get the equations of motion. In the horizontal direction, it can be modeled in (13).

$$\vec{v} = \vec{v}_0 + \int_0^t \vec{g}\, dt = \vec{v}_0 + \vec{v}\, t \quad (13)$$

The equation for the vertical direction is as (14) and (15).

$$\vec{r} = \vec{r}_0 + \int_0^t (\vec{r}_0 + \vec{g}t)\, dt = \vec{r}_0 + \vec{v}_0 t + \frac{1}{2}\vec{g}\, r^2 \quad (14)$$

$$\vec{r}_0 = \vec{0} \quad (15)$$

In (16) and (17) each of which is a vector equation of location and velocity.

$$\vec{v}_0 = v_0 \cos(\alpha) t\, \vec{j} + \left((v_0 \sin(\alpha) t - \frac{1}{2} g t^2\right) \quad (16)$$

$$\vec{v} = \vec{r} = (v_0 \cos(\alpha))\, \vec{j} + ((v_0 \sin(\alpha) - gt)\vec{k} \quad (17)$$

Lastly, the trajectory has the following expression as (18).

$$\overrightarrow{x_1}(t+1) = \left[v_0 \cos\left(\alpha \frac{t}{M_{iter}}\right) + \varepsilon\right] \overrightarrow{x_{best}}(t) + \left[v_0 \sin\left(\alpha \frac{\alpha t}{M_{iter}}\right) - g + \varepsilon\right] \overrightarrow{x_i}(t) \quad (18)$$

Where v_0 is set to 1 seg. α is set to $\frac{\pi}{2}$. ε is set to 1e-6. g is gravity of the earth (0.009807 km/s^2).

2.1.4. Fourth tactic: move to get away

In this tactic, horned lizards make fast, random movements around the environment to avoid predators. The tactic can be formulated in (19).

$$\overrightarrow{x_1}(t+1) = \overrightarrow{x_{best}}(t) + walk\left(\frac{1}{2} - \varepsilon\right) \overrightarrow{x_i}(t) \quad (19)$$

2.1.5. Fifth tactic: ∝- melanophore stimulating hormone

Horned lizard skin can change skin by rotating due to the influence of temperature on the ∝-melanophore stimulating hormone. This tactical formula is formulated in (20).

$$melanophore(i) = \frac{Fitness_{max} - Fitness(i)}{Fitness_{max} - Fitness_{min}} \quad (20)$$

Where $Fitness_{max}$ and $Fitness_{min}$ are the worst and best ftness value in the current t generation. After calculating (20), the $melanophore(i)$ value vector is normalized within the interval [0, 1]. In (21), search agents are replaced by a low $\propto -MSH$ rate, less than 0.3.

$$\overrightarrow{x_1}(t) = \overrightarrow{x_{best}}(t) + \frac{1}{2}\left[\overrightarrow{x_{r1}}(t) - (-1)^{\sigma} \overrightarrow{x_{r2}}(t)\right] \quad (21)$$

2.2. DC motor

In this part, a linear model of a DC motor is created using the mechanical and electrical equations in conjunction. There is an explanation of mathematical models and model concepts. The model's correctness is the main factor in control design. Efficiency is increased, and time and money are saved. The idea of creating the ideal model is a crucial first step. The image in Figure 1 illustrates the widely recognized principle of DC motor modeling: the integration of electrical and mechanical equations.

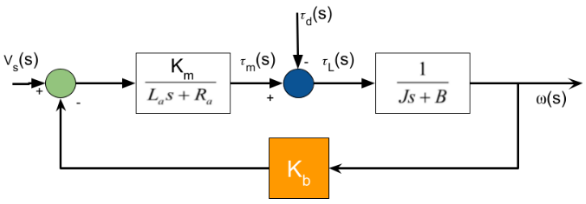

Figure 1. The DC motor schematic [25]

2.3. Horned lizard optimization algorithm-aquila optimizer

This article presents a modification of HLOA using the aquila optimizer equation. The ex is used to control the extended search (exploration) through the number of iterations and can be formulated in (22).

$$ex = \left(1 - \frac{t}{T}\right) \quad (22)$$

Additionally, the mean value of the current solution connected at the t -th iteration is applied and can be formulated in (23).

$$X_M(t) = \frac{1}{N}\sum_{i=1}^{N} X_i(t), \forall j = 1,2 \ldots . Dim \quad (23)$$

This research modifies (10) by adding (22) and (23). So, it can be formulated as (24).

$$\overrightarrow{x_1}(t+1) = \left(\overrightarrow{x_{best}}(t) * ex + X_M(t)\right) + \left(\delta - \frac{\delta.t}{M_{iter}}\right)$$

$$[C_1[\sin(\overrightarrow{x_{r1}}(t)) - C_1\cos(\overrightarrow{x_{r2}}(t))] - (-1)^{\sigma}(\cos(\overrightarrow{x_{r3}}(t)) - \sin(\overrightarrow{x_{r4}}(t)))] \tag{24}$$

3. THE PROPOSED HLAO FOR TUNING PID IN DC MOTOR

This research aims to improve HLO capabilities by adding the aquila optimizer method. The proposed method is used to obtain PID parameters for adaptive control of DC motors. To obtain the ideal temporary response point, the steps illustrated in Figure 2 are carried out. The initial step follows the flow of the HLO method to (10). In (10), it is changed using the (24).

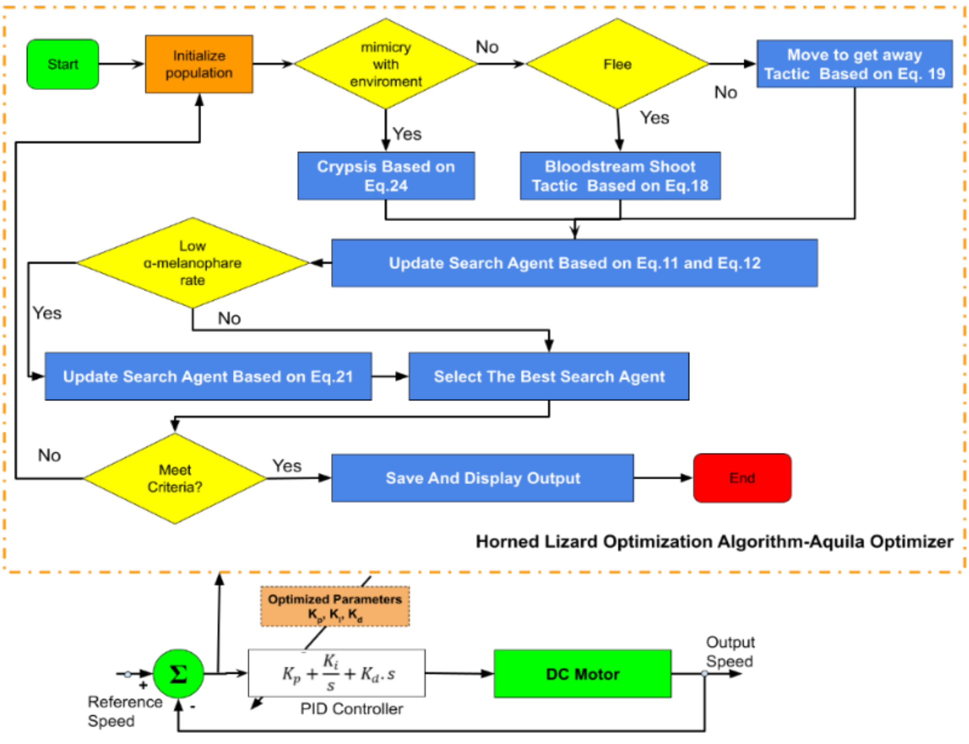

Figure 2. Proposed of HLAO for DC motor

4. RESULTS AND DISCUSSION

4.1. Convergence curve profile

To run simulations and write code, a laptop with an Intel I5-5200 2.19 GHz processor specification and 8 GB of RAM memory is utilized together with a MATLAB/Simulink program. The benchmark function is used to measure the HLAO algorithm's performance. This is to ascertain how well the suggested approach performs. 23 functions make up the benchmark function. Ten fixed-dimensional multimodal functions (F14–F23), six multimodal functions (F8–F13), and seven unimodal functions (F1–F7) make up the mathematical function. An illustration of the convergence curve can be seen in Figures 3(a) to 3(w).

The performance of HLAO and rival algorithms are statistically analyzed to see if HLAO has a statistically significant edge over the other algorithms. The mean rank value of any algorithm can be found by knowing the rank of each function. The statistical analysis for each function is displayed in Table 1. A rating is a figure that represents the best mean value. HLAO has a value of 1, as indicated by the total rank value for each algorithm. The rank value on average is 1.217391304. A comparison of the ranks of unimodal algorithm functions is shown in Table 2. In multimodal, HLAO has rank 1. Table 3 presents a comparison of the multimodal functions that were employed in terms of ranks. A comparison of fixed-multimodal ranks between HLO and HLAO is shown in Table 4.

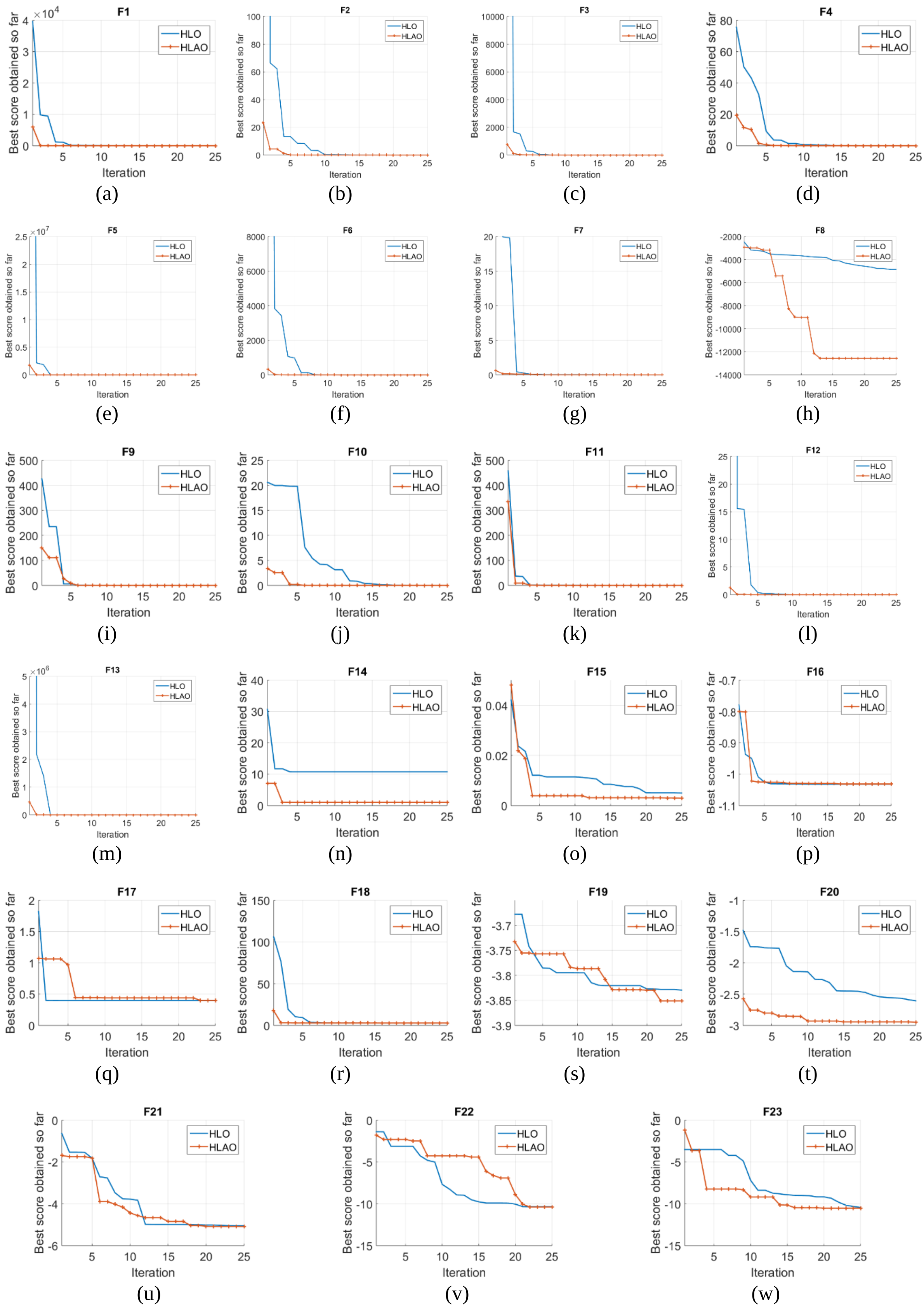

Figure 3. Convergence curve of benchmark function: (a) F1, (b) F2, (c) F3, (d) F4, (e) F5, (f) F6, (g) F7, (h) F8, (i) F9, (j) F10, (k) F11, (l) F12, (m) F13, (n) F14, (o) F15, (p) F16, (q) F17, (r) F18, (s) F19, (t) F20, (u) F21, (v) F22, and (w) F23

Table 1. Comparison of HLAO and HLO

Function		HLAO	HLO	Function		HLAO	HLO
F1	Best	6.25E-22	1.81E-17	F13	Best	1.54E-09	3.82E-02
	Mean	1.97E-17	1.39E-12		Mean	2.52E-05	7.89E-01
	Worst	3.83E-16	2.33E-11		Worst	2.59E-04	2.99E+00
	Std	6.30E-17	3.95E-12		Std	5.02E-05	7.02E-01
	Rank	1	2		Rank	1	2
F2	Best	1.85E-11	1.59E-08	F14	Best	9.98E-01	9.98E-01
	Mean	1.11E-08	5.50E-07		Mean	3.42E+00	4.26E+00
	Worst	1.52E-07	3.25E-06		Worst	1.27E+01	1.27E+01
	Std	2.38E-08	7.38E-07		Std	3.38E+00	3.41E+00
	Rank	1	2		Rank	2	1
F3	Best	6.64E-22	1.75E-17	F15	Best	0.000316	0.000371
	Mean	1.20E-15	3.01E-12		Mean	0.007814	0.010506
	Worst	4.43E-14	4.93E-11		Worst	0.025807	0.088158
	Std	6.26E-15	9.98E-12		Std	0.008761	0.014468
	Rank	1	2		Rank	1	2
F4	Best	2.12E-12	2.03E-09	F16	Best	-1.03E+00	-1.03E+00
	Mean	5.18E-10	2.75E-07		Mean	-1.03E+00	-1.03E+00
	Worst	5.04E-09	2.28E-06		Worst	-1.03E+00	-1.03E+00
	Std	8.57E-10	4.13E-07		Std	4.52E-04	1.13E-04
	Rank	1	2		Rank	1	1
F5	Best	0.000443	28.697	F17	Best	3.98E-01	3.98E-01
	Mean	25.2614	28.7412		Mean	4.03E-01	3.98E-01
	Worst	28.707	28.8937		Worst	4.88E-01	3.98E-01
	Std	9.4194	0.04439		Std	1.32E-02	3.13E-05
	Rank	1	2		Rank	1	2
F6	Best	9.06E-09	0.002026	F18	Best	3.00E+00	3.00E+00
	Mean	0.001114	0.045772		Mean	5.76E+00	5.16E+00
	Worst	0.008468	0.11159		Worst	8.45E+01	8.40E+01
	Std	0.002034	0.02865		Std	1.26E+01	1.20E+01
	Rank	1	2		Rank	2	1
F7	Best	6.23E-05	1.44E-05	F19	Best	-3.86E+00	-3.86E+00
	Mean	0.00365	0.003612		Mean	-3.83E+00	-3.84E+00
	Worst	0.015079	0.01278		Worst	-3.09E+00	-3.57E+00
	Std	0.00356	0.002988		Std	1.11E-01	5.10E-02
	Rank	2	1		Rank	1	2
F8	Best	-12569.5	-7274.41	F20	Best	-3.3149	-3.3126
	Mean	-5376.16	-5727.71		Mean	-3.1401	-3.1088
	Worst	-2852.61	-3942.41		Worst	-2.7796	-2.515
	Std	2809.739	876.9446		Std	0.12151	0.16389
	Rank	2	1		Rank	1	2
F9	Best	0	0	F21	Best	-10.1531	-10.1524
	Mean	0.59704	1.96E-08		Mean	-10.1229	-8.1081
	Worst	29.8513	9.79E-07		Worst	-9.8836	-2.5731
	Std	4.2216	1.39E-07		Std	0.050521	3.0475
	Rank	2	1		Rank	1	2
F10	Best	4.84E-13	1.08E-08	F22	Best	-10.4028	-10.401
	Mean	1.90E-09	3.60E-07		Mean	-10.1759	-8.6926
	Worst	3.79E-08	3.14E-06		Worst	-5.0875	-1.8246
	Std	5.79E-09	5.83E-07		Std	0.79866	2.7727
	Rank	1	2		Rank	1	2
F11	Best	0.00E+00	0.00E+00	F23	Best	-10.5363	-10.5361
	Mean	2.22E-18	2.65E-13		Mean	-9.9883	-7.7724
	Worst	1.11E-16	5.26E-12		Worst	-1.6572	-1.8395
	Std	1.57E-17	8.27E-13		Std	1.9386	3.3378
	Rank	1	2		Rank	1	2
F12	Best	1.34E-08	1.96E-04				
	Mean	3.54E-04	5.30E-02	Sum Rank		28	40
	Worst	1.23E-02	7.18E-01	Mean Rank		1.217391304	1.739130435
	Std	1.73E-03	1.30E-01				
	Rank	1	2				

Table 2. Rank comparison of unimodal functions between algorithms (F1-F7)

Function	HLAO	HLO
Sum Rank	8	13
Mean Rank	1.1428571	1.8571429
Total Rank	1	2

Table 3. Rank comparison of multimodal functions between algorithms (F8-F13)

Function	HLAO	HLO
Sum Rank	8	10
Mean Rank	1.3333333	1.6666667
Total Rank	1	2

Table 4. Rank comparison of fixed-multimodal functions between algorithms (F14-F23)

Function	HLAO	HLO
Sum Rank	12	17
Mean Rank	1.2	1.7
Total Rank	1	2

4.2. Implementing HLAO for DC motor

PID-based DC motor control necessitates exact and accurate parameter adjustment. To obtain optimal PID parameters through the implementation of HLAO, its performance must also be verified. Figure 4 shows the outcomes of the PID control for DC motors using HLAO. A control's performance can be evaluated using a variety of theories. Several widely recognized theories, include integral of time-weighted absolute error (ITAE) and integrated of time-weighted squared error (ITSE). ITSE and ITAE are utilized as performance validation in this work.

$$ITSE = \int_0^\infty t.e^2(t).dt \tag{25}$$

$$ITAE = \int_0^\infty t.e(t).dt \tag{26}$$

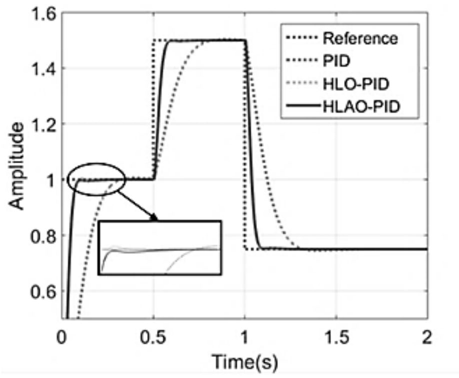

Figure 4. The response of DC motor

By testing the HLAO-based PID on a DC motor with a reference speed of 1 pu, the ITSE from HLAO-PID is 0.0033. This value is 89.25 and 5.7143% better than PID and HLO-PID. Meanwhile, the overshoot value of HLAO-PID is better by the detailed results of the performance tests for each algorithm can be seen in Table 5.

Table 5. Response DC motor with PID

Controller	Overshoot	Rise Time	Settling Time	ITSE	ITAE
PID	1.007	0.18	0.278	0.0307	0.0794
HLO-PID	1.006	0.0465	0.0759	0.0035	0.0076
HLAO-PID	No Overshoot	0.0462	0.0774	0.0033	0.0080

5. CONCLUSION

A metaheuristic optimization method called the HLO algorithm uses mathematics to model various escape strategies such as crypsis, skin lightening or darkening, blood spraying, and cellular defense mechanisms. The improved HLO by modifying the additional functions of the aquila optimizer increases the performance of the HLO. This hybrid method is called HLAO. This research validates the performance of HLAO using performance tests on CEC2017 benchmark functions and DC motors. From the simulation on the CEC2017 benchmark function, it was found that the performance of HLAO has more promising exploration and exploitation capabilities. Testing on DC motors, it was found that the HLAO-PID method could reduce overshoot. In addition, HLAO-PID has the best ITSE score. The ITSE value of HLOA is 89.25% and 5.7143% better than PID and HLO-PID. This research can be developed further by using a variety of other methods and using more complex objects.

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